

# UC Santa Cruz

## UC Santa Cruz Previously Published Works

**Title**

Parametric face drawings: A demographically diverse and customizable face space model.

**Permalink**

<https://escholarship.org/uc/item/2d07118s>

**Journal**

Journal of vision, 19(11)

**ISSN**

1534-7362

**Authors**

Day, Jennifer  
Davidenko, Nicolas

**Publication Date**

2019-09-01

**DOI**

10.1167/19.11.7

Peer reviewed

# Parametric face drawings: A demographically diverse and customizable face space model

Jennifer Day

Department of Psychology, University of California,  
Santa Cruz, CA, USA

Nicolas Davidenko

Department of Psychology, University of California,  
Santa Cruz, CA, USA



We introduce a novel face space model—parametric face drawings (or PFDs)—to generate schematic, though realistic, parameterized line drawings of faces based on the statistical distribution of human facial features. A review of existing face space models (including FaceGen Modeller, Synthetic Faces, MPI, and active appearance model) indicates that current models are constrained by their reliance on ethnically homogeneous face databases. This constraint has led to negative consequences for underrepresented populations, such as impairments in automatized identity recognition of certain demographic groups. Our model is based on a demographically diverse sample of 400 faces (200 female, 200 male; 100 East Asian/Pacific Islander, 100 Latinx/Hispanic, 100 black/African-American, and 100 white/Caucasian) compiled from several face databases (including FERET face recognition technology and the Chicago Face Database). Each front-view face image is manually coded with 85 landmark points that are then normalized and rendered with MATLAB (MathWorks, Natick, MA) tools to produce a smooth, parameterized face line drawing. We present data from two behavioral experiments to validate our model and demonstrate its applicability. In Experiment 1 we show that PFDs produce a reliable “inversion effect” in short-term recognition, a hallmark of holistic processing. In Experiment 2, we conduct a celebrity recognition task, comparing performance on PFDs to performance on untextured renderings from FaceGen Modeller. Participants successfully recognized approximately 50% of celebrity faces based on the PFD models, comparable to performance based on FaceGen Modeller (also 50% correct). We highlight a range of potential applications of our model, list some limitations, and provide MATLAB resources for researchers to utilize our face space, including the ability to customize the demographic makeup of the face space, add new faces, and produce morphs and caricatures.

## Introduction

Face space (Valentine, 1991) is theoretical framework wherein individual faces are encoded as points in multidimensional space, where the location of a point provides an appropriate parallel to the mental representation of the corresponding face. Among the assumptions of the face space framework are that (1) the dimensions represent physiognomic features used to encode faces, (2) the Euclidean distance between two points in the space reflects the dissimilarity between the two corresponding faces, (3) the majority of represented faces are own-race faces, (4) the center of face space is densely populated, and (5) the average (or *norm*) face represents a uniquely neutral face to the individual.

Although most researchers agree on these basic assumptions, there are two competing schools of thought about how faces are encoded relative to the norm: norm-based representations (Rhodes, Brennan, & Carey, 1987; Leopold, O’Toole, Vetter, & Blanz, 2001) and exemplar-based representations (Storrs & Arnold, 2012; Cronin, Spence, Miller, & Arnold, 2017). Norm-based representations assume that the norm, or average face, is used explicitly as a reference for coding other faces in the space; each face is thought to be coded as a particular angular deviation from the norm with a particular distance or eccentricity that represents the face’s distinctiveness or identity strength. In contrast, exemplar-based representations do not assume that the norm is represented explicitly, but rather arises as a statistical property of the centrally dense distribution of faces. Here, a face is encoded relative to its local neighbors, without explicit reference to a norm (Valentine, 1991).

Since Valentine’s (1991) theoretical framework was proposed, many studies have tested the degree to which face space is an accurate representation of how faces

Citation: Day, J., & Davidenko, N. (2019). Parametric face drawings: A demographically diverse and customizable face space model. *Journal of Vision*, 19(11):7, 1–12, <https://doi.org/10.1167/19.11.7>.

<https://doi.org/10.1167/19.11.7>

Received January 21, 2019; published September 18, 2019

ISSN 1534-7362 Copyright 2019 The Authors



are organized in a person's own psychological space. Busey (1998) discussed how image processing techniques that allow for morphing between different identities are only useful if the physical image transformations preserve the perceptual relationships between faces. For example, morphing between two "parent" face identities should produce a face that lies in the trajectory between the two parents; however, behavioral ratings and multidimensional scaling (MDS; see Shepard, 1962) don't bear this out, as morphed faces often lose details of the parent faces due to smoothing artefacts, and thus appear younger, more average, and more attractive than either of the parent faces.

Theoretical and physical work by Parke (1974); Jones and Poggio (1996); Ezzat and Poggio (1996); DeCarlos, Metaxas, and Stone (1998); and Cootes, Edwards, and Taylor (1998) created the foundation for a face space. In 1999, Blanz and Vetter created a concrete, "physical" face space by laser scanning real human faces and creating smooth, three-dimensional (3D) models. In their face space, novel face exemplars could be generated from the sample exemplars by separately adjusting the 3D shape and texture parameters. Applying principal components analysis (PCA) to the resulting dimensions produced a set of *eigen-faces*, candidate dimensions for face representations. Following Blanz and Vetter's (1999) work, other researchers (Wilson, Loffler, & Wilkinson, 2002; Davidenko, 2007; Chang & Tsao, 2017) have generated physical face space models based on the distribution of "real" face stimuli. Although the resulting dimensions vary from study to study, they tend to describe global and configural properties of faces (e.g., adiposity, protrusion of the forehead and chin, distance between the eyes), rather than individual features. Wilson et al. (2002) created a "synthetic face space" based on images of real faces. Each face was coded with 37 landmark points based on radial measurements at equally spaced angles around the head (including hairline and head shape). The low dimensionality of this space facilitated the process of coding faces and describing the underlying dimensions. However, two major limitations of the synthetic face space were the use of generic features (e.g., eyes and mouth) that did not differ across individual faces, and the low number and racial homogeneity of the faces included in the space. Given that the eyes and mouth contribute strongly to face identification (see Schyns, Bonnar, & Gosselin, 2002; Smith, Cottrell, Gosselin, & Schyns, 2005), this method is limited in its applicability to realistic face recognition behavior. Later, Davidenko (2007) created a similar landmark-based face space to describe the variability of profile face silhouettes. This model was based on the manual coding of 18 keypoint locations (36 XY coordinates) on a large number of profile face images.

A PCA revealed the underlying dimensions of the space, and behavioral ratings confirmed that the space can be effectively described by its first 20 dimensions. Although the method did not rely on using prespecified generic facial features, it was limited by the lack of texture information and feature details about the eyes, nose, and mouth.

FaceGen Modeller (<https://facegen.com>) is another popularly used model to create face stimuli, as it allows users to generate realistic 3D faces based on an underlying database of coded faces. Although FaceGen is widely used in research (Oosterhof & Todorov, 2009; Hershfield et al., 2011; Olivola & Todorov, 2010; Davidenko, Vu, Heller, & Collins, 2016), the method is opaque regarding the independent parameters that define the model. Although FaceGen is based on Blanz and Vetter (1999), the specific methodology and database has not been published. Furthermore, the sampling of faces is highly white-skewed (of the 273 faces, 67.28% are European, 10.66% East Asian, 2.94% South Asian, and 9.56% African). The inability to modify the database of sampled faces or to inspect the underlying dimensions of the space restricts the model's generalizability, especially for modeling non-white populations.

Since then, other researchers have developed more complex and realistic face space models that approach the realism of actual human faces. Recently, Chang and Tsao (2017) developed realistic parametrized face stimuli with images of faces from the FEI (Faculty of Industrial Engineering) face database based on the active appearance model (similar to Blanz and Vetter, 1999). Landmark points were manually coded for each face and smoothed into an outline of the face and key features without textural information. Separate PCAs were performed on the outline shapes and the internal textural information separately, to produce 25 dimensions each, for a total of 50 dimensions. Another recent model, the Diversity in Faces dataset (Merler, Ratha, Feris, & Smith, 2019) provides a dataset of a million annotated human face images from diverse populations. Although these face spaces provide promising tools for studying facial identity and variation, their main limitation is that other researchers cannot modify the space by adding new faces. As a result, the resulting face spaces are bound to the populations captured in the model, and cannot be extended by individual researchers to study other face populations, such as infant faces, elderly faces, or specific faces familiar to a participant.

### **Parametric face drawings (PFDs) as an approach to deal with current limitations of racial bias, code accessibility, and texture-based artefacts**

The face space we introduce in this paper attempts to address the limitations of the current face spaces

available to researchers. Parametric face drawings (PFDs) are a shape-based parameterization of front-view faces, using a landmark annotation approach similar to the one described in Davidenko (2007). The advantages of the PFD model are that (1) it is based on a demographically diverse set of 400 faces sampled equally across four major racial groups (East Asian/Pacific Islander, Latinx/Hispanic, black/African-American, and white/Caucasian) and two genders, (2) we are releasing the source code for individual researchers to modify the space by adding or subtracting faces according to the desired demographic makeup for researchers' experimental purposes, and (3) it provides a simple, shape-based face schematic space that allows for easy rendering of face drawing stimuli with existing MATLAB tools, avoids morphing artefacts due to blending textures, and provides a direct approach to study the cognitive and visual processes in recognizing and producing face drawings.

First, our PFD model provides a diverse and balanced set of faces sampled across four races and two genders. Depending on individual researchers' needs, the face space dimensions can be constructed based on a subset of these faces (for example, creating a face space based primarily on Latinx faces), or expanded to include additional demographic groups or faces of different ages.

One of the clearest advantages of the PFD space is its availability, ease of use, and customization. Unlike more realistic parametric face spaces (e.g. FaceGen, and Chang & Tsao, 2017), the PFD can be easily modified or expanded by individual researchers by adding or removing faces and manually coding new faces into the space. Critically, because PFDs are not sensitive to textural information, researchers can add any front view face to the space, regardless of lighting conditions or other image properties that typically constrain complex texture-based face space. In addition, we have released the source code for encoding new face stimuli into the model and rendering arbitrary faces for experimental study. Our model is fully available online, and instructions for coding new faces are provided on the Open Science Framework (OSF) (<https://osf.io/6uds5/>).

Finally, because the renderings are shape-based and do not include complex texture information, PFDs address the limitations raised by Busey (1998); when creating caricatures or morphs between two identities, the resulting faces do not suffer from blending artefacts associated with other models that include texture. A further advantage of using lines to represent facial regions and features is an increased tolerance of caricatures; that is caricatures and “extreme” faces can be created without unrealistic image artefacts due to morphing texture information. In the discussion we also describe the benefits of this model for studying face drawing (see also Day & Davidenko, 2018).

## Methods

### Constructing parametric face drawings

PFDs are rendered as smooth line drawings that include the outline of the face, the eyes, eyebrows, nose, and mouth (see Figure 1). The space is constructed based on 400 face identities, each of which has been manually coded by research assistants by identifying 85 keypoints. The set of 85 key points were chosen based on pilot studies that evaluated the recognizability of celebrity faces based on different number of points (see Day & Davidenko, 2018). After the 85 points are coded, their coordinates are normalized to a standard position by scaling, rotation, and translation, such that the two pupils are located at [0,0] and [2,0]. After excluding the noninformative pupil points, the coordinates of the remaining 83 keypoints (166 x-y values) are rendered using MATLAB graphing functions to spline, fill, and plot individual features and create a parametric face drawing (PFD; see Figure 1). The distribution of 166 informative x-y coordinates across the 400 faces is entered into a PCA to reveal orthogonal dimensions that best explain the variability of the face exemplars. Importantly, the renderings do not rely on any texture information present in the face image. As such, *any* front-facing face image is a candidate for inclusion in the face space.

The face identities included in our PFD model are sampled from the following: FERET, Utrecht face database, Mugshot database, 10k U.S. Adult Faces Database, Chicago Face Database, and pictures of University of California, Santa Cruz, (UCSC) students, chosen to represent a demographically diverse sample of faces. The space is equally balanced between male and female faces, and across four racial groups; East Asian/Pacific Islander, Latinx/Hispanic, black/African-American, and white/Caucasian. The sample includes adult faces (18–65 years of age, with a mean age of 30.7 years), although the distribution of ages is not equal across all races and genders. The balanced distribution of gender and race results in face-space dimensions (principal components, or PCs) that are representative of all groups equally, rather than biased toward white/Caucasian faces, which is the case in practically all existing face space models. Figure 2 shows the effects of varying the coefficients of the first 6 PCs in the rendered faces. Figure 3 shows the distribution of faces along the first 2 PCs based on gender and race.

On the OSF page for this project (<https://osf.io/6uds5/>), we provide MATLAB tools for rendering PFDs; constructing averages, morphs, and caricatures; generating new identities; and computing the variability within and across groups of faces. An individual face can be represented as a single point in the 166-dimensional face space, as an “identity vector” of PC





Figure 1. Two examples of front-view faces that are parameterized with 85 key points, normalized, and rendered using MATLAB plot, fill, and spline functions. Face images are used with permission from the Chicago Face Database.

coefficients. An all-0 vector represents the average face, and caricatures can be constructed by scaling identity vectors away from the average face (see Figure 4). Morphs can be constructed as weighted sums of “parent” faces. Because PFDs do not carry texture information, morphs are not vulnerable to blending artefacts present in other models. Finally, PFDs are also generative, allowing researchers to easily construct realistic identities based on the distribution of existing faces. Because the PCA dimensions are normally distributed, new faces can be generated by assigning normally distributed random values to each of the 166 dimensions, scaled by the standard deviation of each PC, which creates artificial but realistic looking faces (see Figure 5). Although the space has 166 dimensions (based on the x-y coordinates of the 83 informative key points), Figure 6 shows that face identities are very well characterized with just the first 60 dimensions. Therefore, the PFD face space is approximately 60-dimensional for practical purposes.

On the OSF page for this project (<https://osf.io/6uds5/>), we have also provided instructions to modify the underlying face space. Specifically, we describe how to add or delete faces from the database with step-by-step instructions for coding each landmark feature. Furthermore, we provide a set of MATLAB tools

allowing individual researchers to expand or modify the face space to represent different target populations.

The utility of a face space depends largely on the perceptual properties of the stimuli. As such, we describe in the following section two experiments intended to validate the PFD stimuli. In Experiment 1, we present data from a short-term recognition task, and demonstrate that PFDs elicit a face inversion effect, a hallmark phenomenon of face processing. In Experiment 2, we assess the amount of personally identifiable information in PFDs by conducting a celebrity recognition study. Our results indicate that PFDs do provide identity information, comparable to that available in the popular FaceGen model based on texture-less renderings.

### Experiment 1: Demonstrating the inversion effect in PFDs

The face inversion effect was first reported by Yin (1969), where people demonstrate superior face processing for upright faces compared to inverted faces. The inversion effect has been used as a hallmark of holistic face processing (Valentine, 1988; Farah, Tanaka, & Drain, 1995). In Experiment 1 we examined whether PFDs elicit a reliable inversion effect.

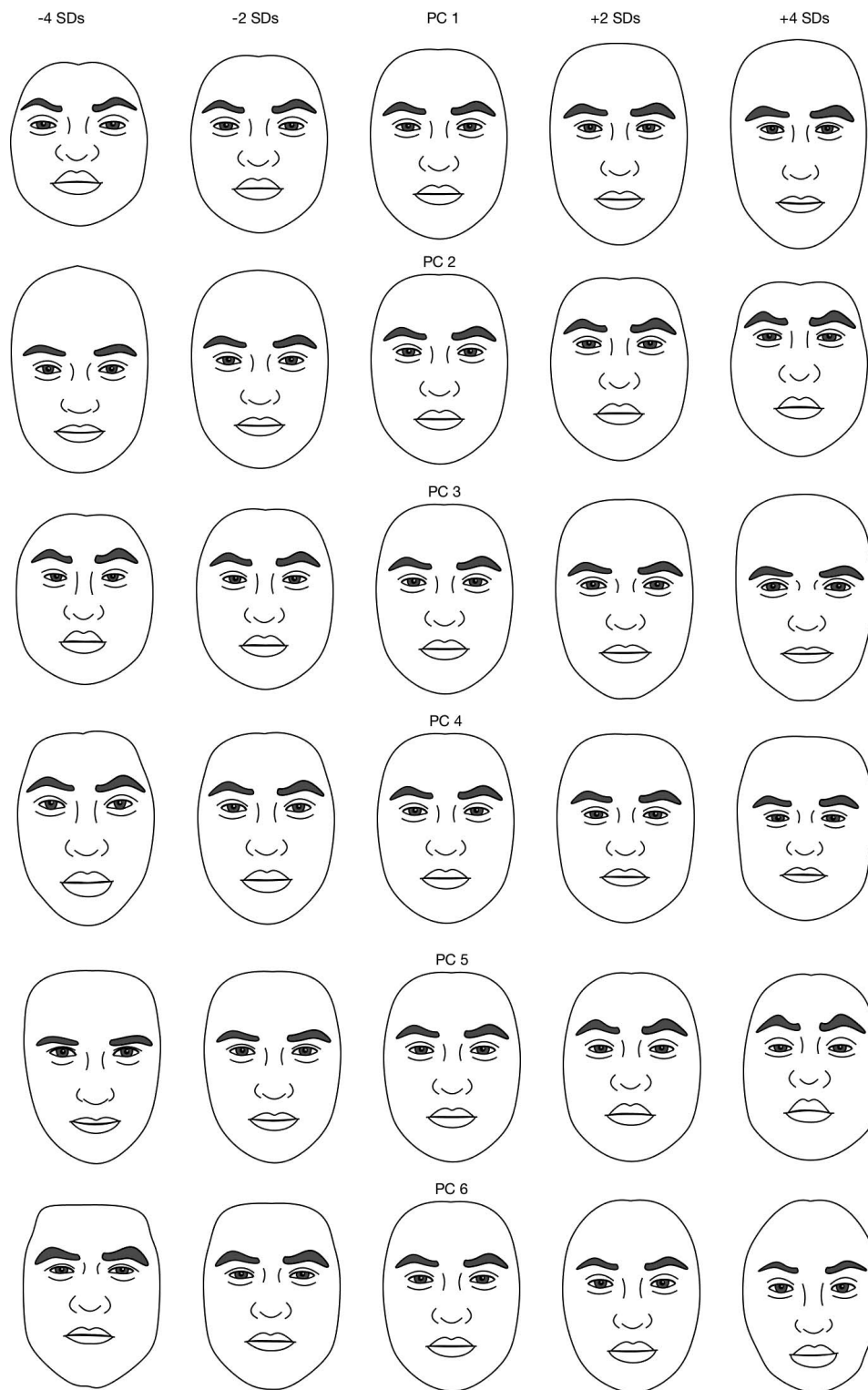


Figure 2. Examples of PFDs varying along the first six principal components (PCs), ranging from  $-4$  standard deviations (STDs) to  $+4$  STDs away from the average face.

### Method

**Participants:** 35 (six male and 29 female) undergraduates at UCSC participated in this experiment in exchange for credit towards a psychology course.

Participants' median age was 18 years, and they identified themselves as Hispanic (34.3%), Asian (25.7%), White (20%), Multiracial (17.1%), or Other (2.9%).

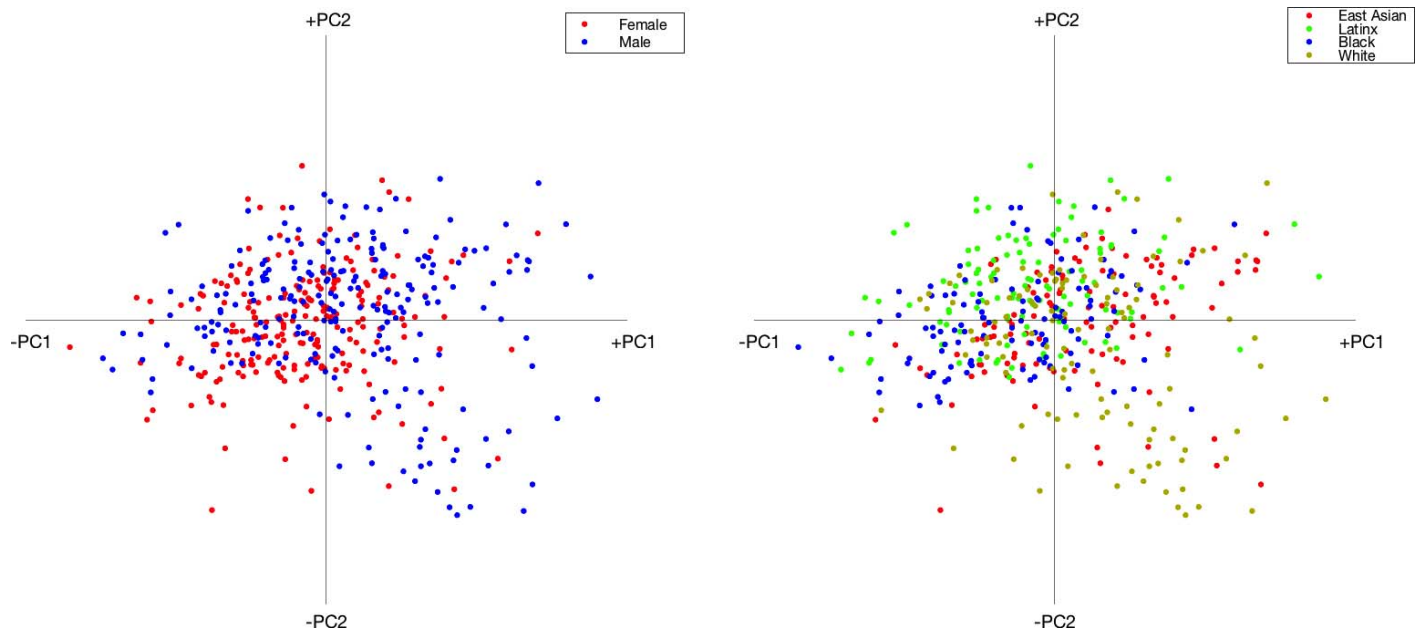


Figure 3. The distribution of faces along the first two principal components (PCs) of face space. Left panel: distribution of female (red) and male (blue) faces along PC1 and PC2; Right panel: distribution of East Asian (red), Latinx (green), black (blue), and white (yellow) faces along PC1 and PC2.

**Stimuli:** For each trial, 80 “centroid” faces were created by selecting 20 normally distributed values as coefficients for the first 20 principal components (PCs) of the face space. These 80 centroid faces were then normalized to have an equal distance from the average face, to ensure no one centroid was more distinctive than another.

For each of the 80 centroid face identities, 3 “vertex” face identities were created by slightly varying the first

20 PC coefficients away from the centroid, setting normally distributed coefficients for PCs 21–30, and then normalizing the distance from the centroid. This ensured that each set of three vertex faces were an equal distance from the identity they were derived from. The 240 vertex faces (80 sets of 3) were the face stimuli used in the experiment.

**Procedure:** In each trial, participants were shown one of the three faces in a vertex group. This served as the

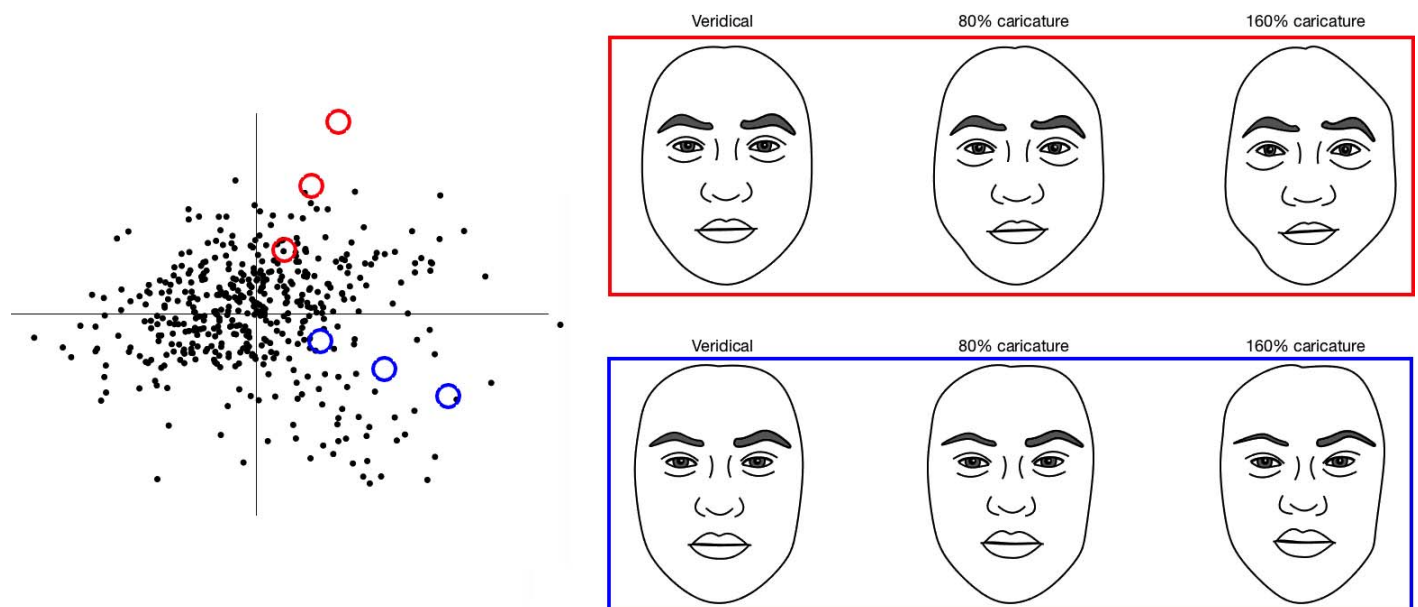


Figure 4. Two examples of caricaturing. From the left (veridical) to the right (160% caricature), faces are defined at ever increasing distances from the average face.

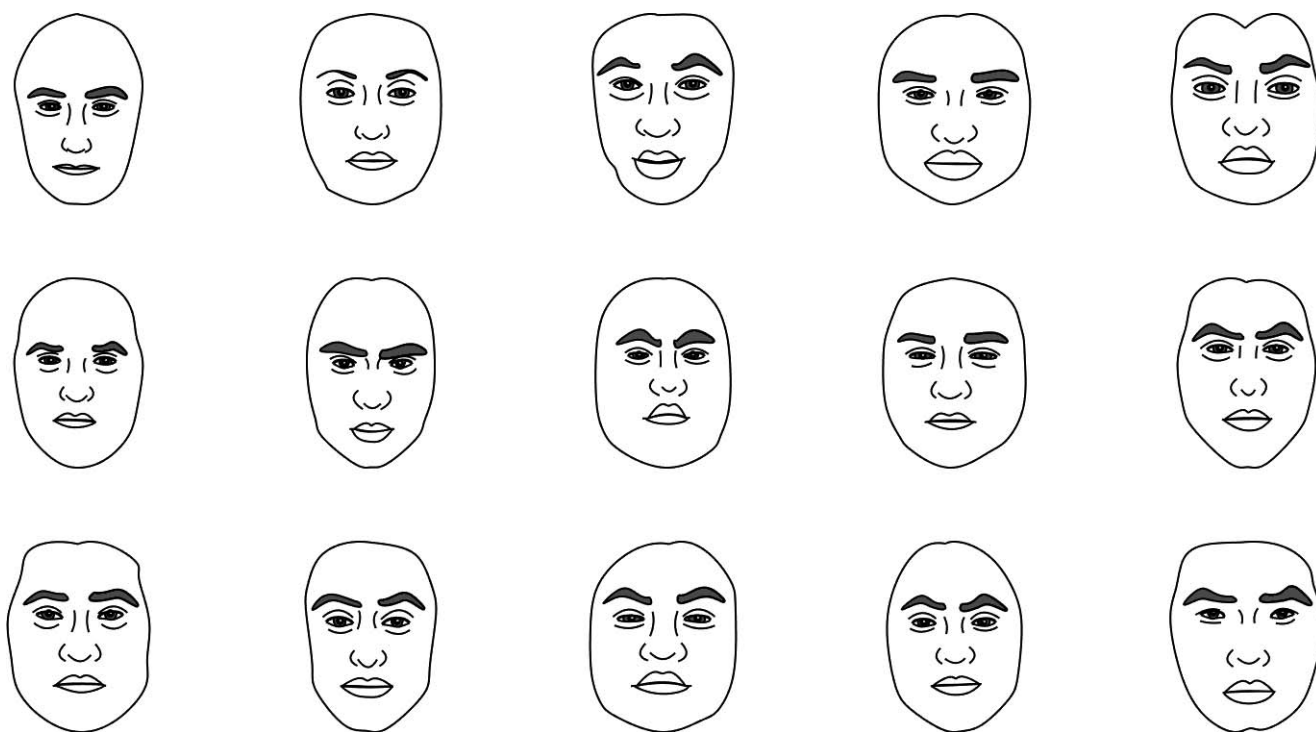


Figure 5. Examples of 15 “random” face identities generated by selecting 50 normally distributed values for the coefficients of the first 50 PCs.

target face to be recognized following a short delay. Each target face was presented either in an upright or inverted orientation for 2 seconds, followed by a jumbled mask for 0.25 seconds and 1.25 second blank interstimulus interval, after which all three vertex faces from the set were presented to the participant in a random arrangement on the screen. The orientation of the three vertex faces was always congruent with that of the studied face, and this was randomly assigned across trials. The three vertex faces stayed on the screen until the participant indicated which one they had previously seen, by pressing the 1, 2, or 3 on the keyboard. The experiment began with three practice trials, where participants were given feedback on their choices. After the three practice trials, the participant completed 80 real trials with no feedback, which included 40 upright trials, and 40 inverted trials, in a random order.

## Results

We measured performance and reaction time on correct trials. We found that there was significantly higher accuracy when faces were upright ( $M = 0.7715$ ,  $SD = 0.0926$ ) over inverted ( $M = 0.7184$ ,  $SD = 0.0969$ ),  $t(32) = 3.777$ ,  $p = 0.00065$  (see Figure 7, left panel). We also found significantly shorter reaction times on correct trials for upright faces ( $M = 2.2142$ ,  $SD = 0.4092$ ) over inverted ( $M = 2.3695$ ,  $SD = 0.5675$ ),  $t(32) = -2.4149$ ,  $p = 0.0216$  (Figure 7, right panel). Together,

these results show that people are faster and more accurate at identifying upright faces. This robust inversion effect replicates the hallmark finding and supports the use of PFDs as face stimuli for research.

## Discussion

We found a reliable inversion effect: participants were better and faster at recognizing upright PFDs than inverted PFDs. The inversion effect indicates that PFD stimuli are processed similarly to faces. The relatively modest effect on performance may be due in part to the nature of PFD stimuli. The faces are rendered as line drawings, which primarily represent high spatial frequency information. Goffaux and Rossion (2006) demonstrated that holistic face processing depends in part on low spatial frequencies. Thus the face inversion effect (which interrupts holistic processing) is likely attenuated by high spatial frequency content in PFD stimuli.

The results of Experiment 1 suggest that PFDs produce an inversion effect, similar to real faces, but how well do PFDs represent personal identity information about a face? To assess the recognizability of individual face identities in PFDs, we designed a celebrity recognition experiment comparing recognition rates between PFDs, untextured renderings from FaceGen Modeller, and the original grayscale celebrity photographs.



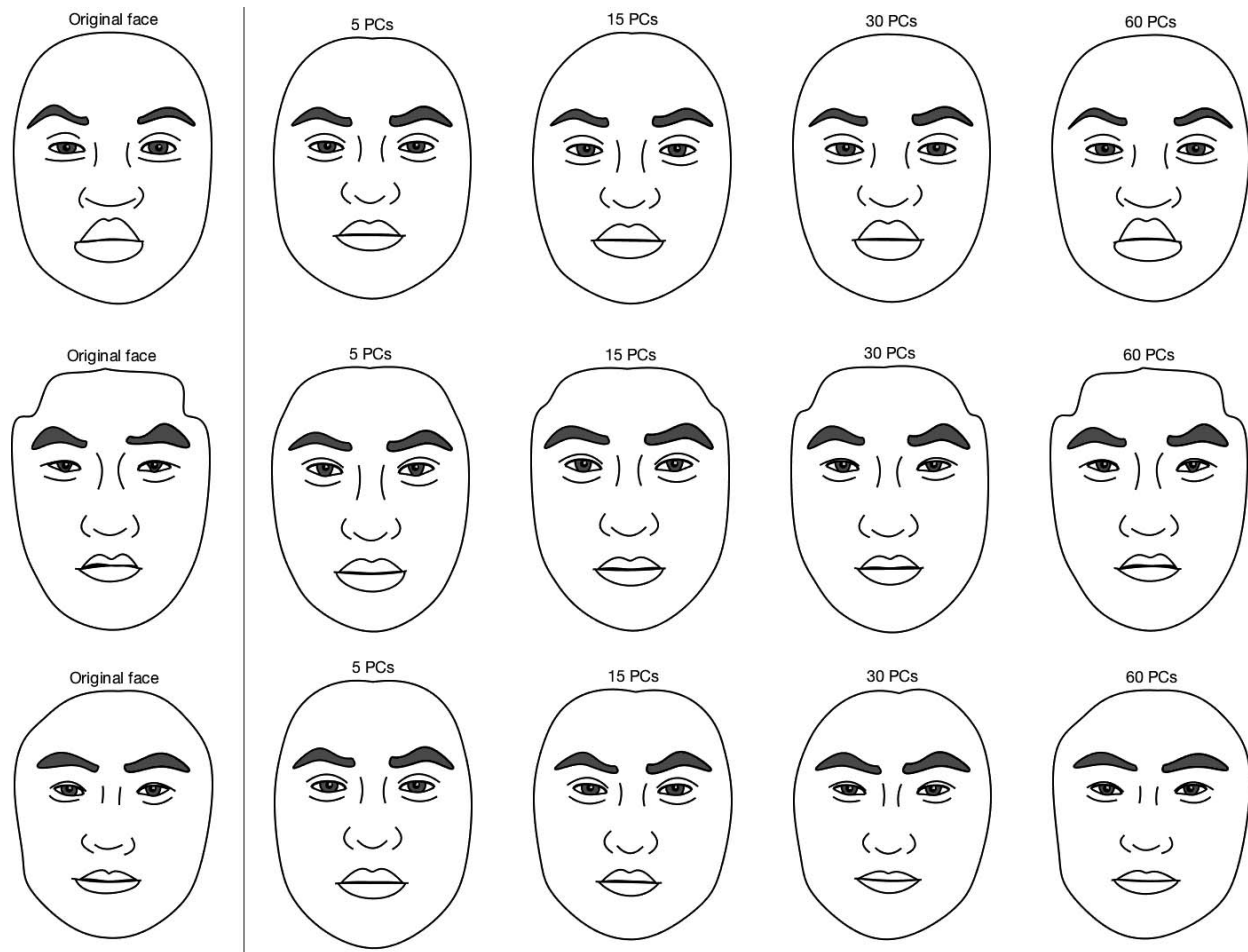


Figure 6. Partial PFDs constructed based on different numbers of principal components (PCs), ranging from five PCs (where only some identity information is preserved) to 60 PCs (where practically all identity information is preserved).

## Experiment 2: Assessing identity recognition in PFDs

A celebrity identity recognition task is ideal to demonstrate how well a model represents identity. By

testing participants' ability to recognize celebrity faces from the PFD renderings, we can assess how much information is preserved for each individual identity. We compared performance on a celebrity recognition task across three different formats of face stimuli:

Face inversion results, N=33

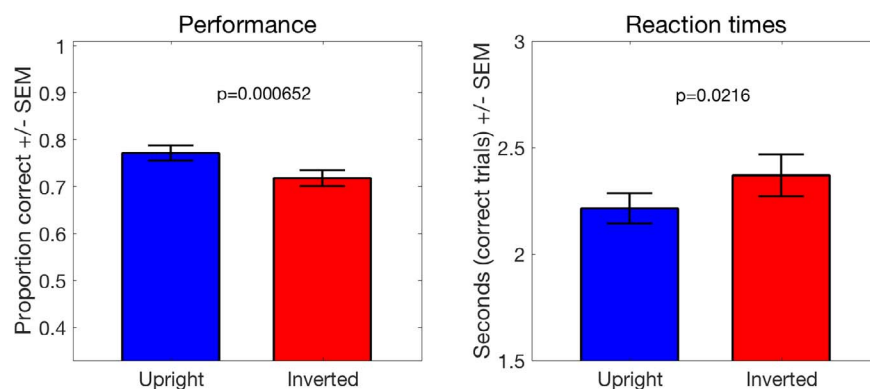


Figure 7. Performance (left panel) and reaction time on correct (right panel) for upright (blue) and inverted (red) faces in a face identification task.

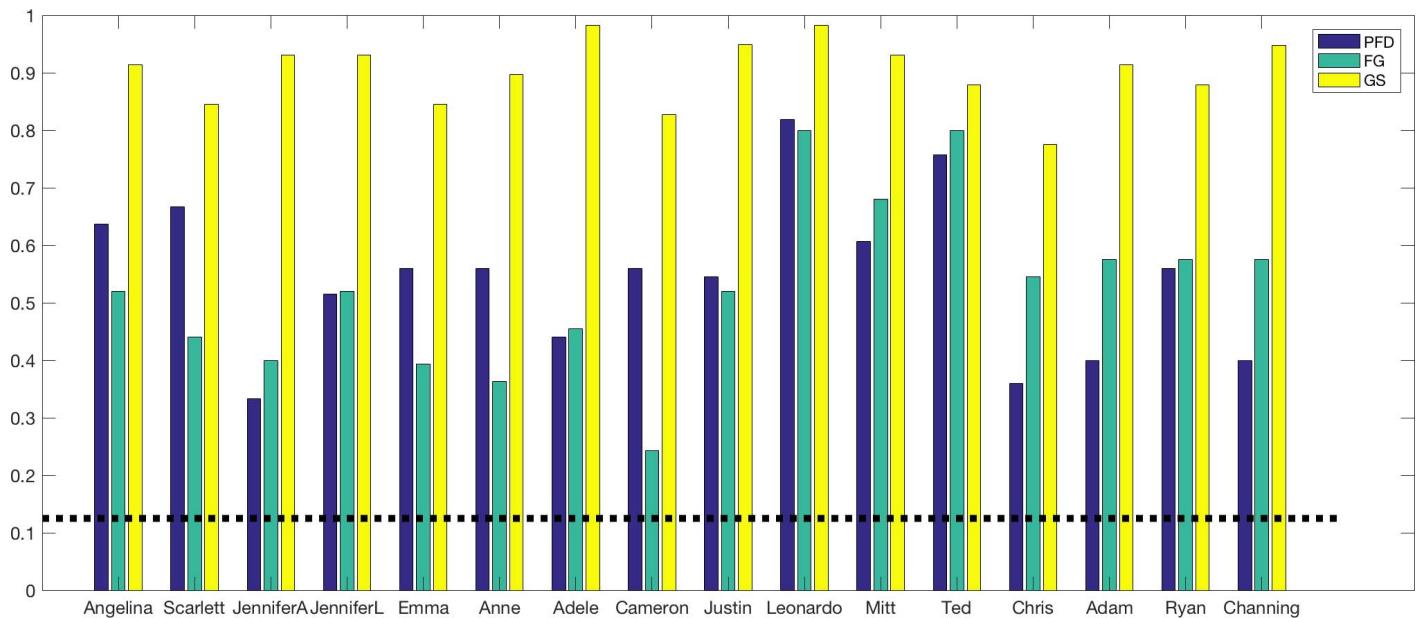


Figure 8. Average score for each celebrity in the celebrity recognition task for parametric face drawings (PFD), FaceGen (FG), and grayscale images of the celebrity (GS).

PFDs, untextured renderings from FaceGen Modeller, and original grayscale photographs to compute a baseline score.

## Method

**Participants:** 58 (12 male, 44 female, and two nonbinary) undergraduates at UCSC participated in this experiment in exchange for credit towards a psychology course. Participants' median age was 21, and they identified themselves as Asian (29.31%), white (27.59%), Hispanic (24.14%), multiracial (18.97%), and other (1.72%). Most participants (87.9%) were raised in the United States. Seven participants were removed for low recognition performance on the grayscale photographs of celebrities.

**Stimuli:** The experiment consisted of a face-to-name matching task using 16 well-known celebrity faces (eight females and eight males). Each participant attempted to recognize eight PFDs, eight FaceGen faces, and then all 16 grayscale photographs to serve as a baseline measure. The order in which PFDs and FaceGen faces were presented was counterbalanced across participants, as well as which eight faces were assigned to be shown in PFD or FaceGen format. To construct the PFDs, photographs of popular celebrity identities were manually coded by research assistants and rendered in MATLAB. FaceGen stimuli were similarly created by uploading the same celebrity photographs into the FaceGen Modeller program, labeling key points, and rendering the faces as an untextured 3D volume. All images (PFDs, FaceGen, and photographs) were shown in grayscale.

**Procedure:** Participants were asked to complete three sheets of an identity recognition task on paper (materials available here: <https://osf.io/6uds5/>). On each sheet, participants were asked to match the celebrity faces (either PFDs, FaceGen, or grayscale images) with their full names. There were four possible orders of presentation, counterbalanced across participants: (1) the first half of the face identities shown first as PFDs and the second half as FaceGen stimuli, (2) the first half of the face identities shown first as FaceGen stimuli and the second half as PFDs, (3) the second half of the face identities shown first as PFDs and the first half as FaceGen stimuli, or (4) the second half of the face identities shown first as FaceGen stimuli and the first half as PFDs. The 16 grayscale photographs were always shown last, and participants were asked to identify all of them to provide a baseline score.

## Results

A one-way repeated measures analysis of variance with a factor of face format (three levels: PFD, FaceGen, photographs) revealed a significant effect of face format on recognition performance [ $F(2, 152) = 65.3$ ,  $p < 0.0001$ ; see Figure 8]. Overall, mean performance on PFDs was 0.5809 correct ( $SE = 0.0324$ ), mean performance on FaceGen faces was 0.5490 correct ( $SE = 0.0384$ ), and mean performance on grayscale photographs was 0.9607 correct ( $SE = 0.0086$ ). Recognition of both PFDs and FaceGen faces was significantly above the chance level of 0.125 [ $t(50) = 12.9234$ ,  $p < 0.0001$  and  $t(50) = 11.7563$ ,  $p < 0.0001$ ,

respectively]. However, there was no statistical difference between performance with PFDs versus FaceGen faces [ $t(50) = 0.64$ ,  $p = 0.53$ ]. Further, a Bayesian paired  $t$ -test analysis revealed support for the null hypothesis that accuracy did not differ between the PFD and FaceGen formats ( $BF_{01} = 5.4$ ). These results indicate that PFDs provide a rich amount of face identity information, comparable to that provided by untextured FaceGen renderings. As such, these stimuli can be used for behavioral studies of identity recognition.

## Discussion

Our results showed that participants performed equally well with PFDs and FaceGen faces on a celebrity recognition task, both substantially above chance levels. The two renderings of face stimuli are created with very different visual information: PFDs are rendered primarily with high spatial frequency (HSF) information, whereas FaceGen faces are rendered as smooth 3D volumes. Nevertheless, we found that PFDs preserve and display identity information to a similar degree as FaceGen renderings. These results suggest PFDs are viable stimuli for identity recognition experiments.

## Discussion

Our experiments with PFDs worked to establish them as viable stimuli for face experiments. The results of Experiment 1 demonstrated a robust inversion effect with PFDs, with upright PFDs being recognized more accurately and faster than inverted PFDs. Experiment 2 further provided evidence that PFDs provide identity information at a level comparable to the popularly used FaceGen Modeller faces. Therefore PFDs can be used in a wide array of face perception experiments and applications, as discussed as follows. We propose that PFDs provide three main benefits compared to existing face space models: demographic diversity, accessibility and customizability of the model, and the simplicity and flexibility of a shape-based rendering.

First, they are based on a demographically diverse sample of faces. Although this should be standard practice in the face perception field, current models are highly ethnically biased, with popular models such as FaceGen being based primarily on white/Caucasian faces. This bias creates problems, such as low-fidelity representation of faces from underrepresented groups. By providing a face space that is equally balanced across four major racial groups, PFD provides a new platform for researchers interested in understanding face recognition across a more diverse population of observers.

A second key advantage of PFDs as experimental stimuli includes the accessibility of the model and flexibility to add new faces into the model. Any front-view face image is a candidate to be encoded into the space, regardless of the particular lighting conditions or image properties. This makes it straightforward for researchers to expand the face space as needed to study face processing in specific demographic groups, as well as to investigate questions of other-race face recognition. The ability to add new faces to the space regardless of lighting, color, or texture information represents increased flexibility for customizing a face space compared to existing models. Researchers can construct their own face spaces to reflect the demographic distribution of the population they are studying. We have made PFDs that are free and available online for face perception researchers. The public database includes demographic information (age, gender, and race) the XY coordinates of the 85 keypoints, and PC coefficients for each of the 400 faces included in the database. In addition, we provide MATLAB scripts for rendering faces and for removing or adding new faces to the space. As mentioned earlier, any front-view face (regardless of lighting, color, size, or textural information) can be added to the space, allowing for the creation of diverse and inclusive face space models.

Finally, the simple, shape-based parameterization avoids issues of blending artefacts associated with more complex texture-based models. Novel PFDs can be generated by modifying an existing identity (e.g., caricaturing), combining multiple identities (i.e., morphing), or randomly generating new identities by sampling normally distributed values for the coefficients of the principal components. The use of simple lines, curves, and bounded shapes to represent features and facial regions allows the creation of morphs that do not have blending issues that otherwise contribute to perceptual judgments of increased attractiveness and decreased age in morphs. As a result, PFDs have increased tolerance for caricaturing, allowing for further deviations of a face away from the average without “breaking” the face information.

One innovative benefit of shape based models is their application to the study of face drawings. The simplicity of PFD stimuli allows for even novice artists to draw them accurately. We recently demonstrated this in a drawing study, where we showed that novice participants are able to more accurately copy upright PFDs compared to inverted PFDs, supporting the view that holistic processing aids in drawing (Day & Davidenko, 2018). Here, the line-based nature of PFDs served as an ideal model for drawing, eliminating complex texture-to-line transformations that typically hinder the accuracy of drawings for novices. In addition, the model provided a direct objective measure

of drawing accuracy. By comparing the face-space distances between target and drawn faces, we could compute a physical measure of accuracy which correlated with perceptual ratings. Future studies can expand on this paradigm to study how and whether novice participants can be trained to draw PFD faces *from memory*, which would provide a new avenue of research in face reconstruction.

## Limitations of the PFD approach

Although the simple, shape-based parameterization can be seen as a methodological advantage, it also carries some limitations. The two main limitations of PFDs as experimental stimuli include (1) the manual coding process and (2) the absence of some important visual properties of faces such as texture, color, and depth information. We list the manual coding of faces as a limitation due to the time cost and possible subjectivity in coding the landmark points. Each face includes 85 landmark points that need to be hand-coded by trained face coders, which takes between 5 and 10 minutes, depending on the coder's experience. To address this limitation, we suggest that this model could be extended to automate the coding of landmark points. Previous work in this field (e.g., Samal & Iyengar, 1992; Jafri & Arabnia, 2009; Amos, Ludwiczuk, & Satyanarayanan, 2016) has produced algorithms that automatically detect these landmark points.

Another limitation is that PFDs do not have all the visual properties that faces do. Since they are coded and rendered as outlines and filled bounded shapes, there is a lack of textural and color information. As such, PFDs preserve HSF information well but do not preserve medium spatial frequency (MSF) or low spatial frequency (LSF) information. The lack of MSFs and LSFs could interfere with some aspects of face processing, such as holistic processing (Goffaux & Rossion, 2006). We also note the lack of hair information as a limitation for identity recognition, but like most face models we excluded hair information to decrease the dimensionality of the space and allow for seamless morphing between faces.

## Conclusion

Despite these limitations, there are many possible applications of the PFD face space model. As discussed previously, a primary benefit of the space is that researchers can customize and add to the space as needed to create representative face spaces for the population they study. For example, a researcher in a largely Hispanic population can customize the space so that it includes more Latinx faces compared to the

other race groups. The resulting dimensions of the space will then reflect the distribution of that particular population (e.g., resulting face-space dimensions will be those that best differentiate faces from that population). Furthermore, the face space allows researchers to calibrate the variability of different groups of faces so that, for instance, black faces are equally variable as white faces when studying the other race effect (Malpass & Kravitz, 1969). The space also allows us to address questions that have to do with variability across sets of faces. For example, what accounts for more variation in face identity—gender or race? Are the dimensions that correlate with gender the same (or similar) across races? Is the variability across male and female faces comparable in different ethnic groups?

Overall, PFDs are a simple and open-source face space model that is available for use and customization by face perception researchers. Despite some limitations, this face space model provides a convenient method for researchers to render realistic looking face drawings to be used in a wide array of face perception experiments.

*Keywords:* parametric faces, schematic face stimuli, physical face space, face drawing

## Acknowledgments

Commercial relationships: none.

Corresponding author: Nicolas Davidenko.

Email: ndaviden@ucsc.edu.

Address: Department of Psychology, University of California, Santa Cruz, CA, USA.

## References

- Amos, B., Ludwiczuk, B., & Satyanarayanan, M. (2016). *Openface: A general-purpose face recognition library with mobile applications*. Unpublished manuscript, Carnegie Mellon University School of Computer Science, Pittsburgh, PA.
- Blanz, V., & Vetter, T. (1999). A morphable model for the synthesis of 3D faces. In *Proceedings of the 26th annual conference on Computer graphics and interactive techniques* (pp. 187–194). New York: ACM Press/Addison-Wesley Publishing Co.
- Busey, T. A. (1998). Physical and psychological representations of faces: Evidence from morphing. *Psychological Science*, 9(6), 476–483.
- Chang, L., & Tsao, D. Y. (2017). The code for facial identity in the primate brain. *Cell*, 169(6), 1013–1028.



- Cootes, T. F., Edwards, G. J., & Taylor, C. J. (1998). Active appearance models. In *European conference on computer vision* (pp. 484–498). Berlin, Heidelberg, Germany: Springer.
- Cronin, S. L., Spence, M. L., Miller, P. A., & Arnold, D. H. (2017). Bidirectional gender face aftereffects: Evidence against normative facial coding. *Perception*, 46(2), 119–138.
- Davidenko, N. (2007). Silhouetted face profiles: A new methodology for face perception research. *Journal of Vision*, 7(4), 6–6.
- Davidenko, N., Vu, C. Q., Heller, N. H., & Collins, J. M. (2016). Attending to race (or gender) does not increase race (or gender) aftereffects. *Frontiers in Psychology*, 7(4):6, 1–17, <https://doi.org/10.1167/7.4.6>. [PubMed] [Article]
- Day, J. A., & Davidenko, N. (2018). Physical and perceptual accuracy of upright and inverted face drawings. *Visual Cognition*, 26(2), 89–99.
- DeCarlo, D., Metaxas, D., & Stone, M. (1998). An anthropometric face model using variational techniques. In *SIGGRAPH*, 98, 67–74.
- Ezzat, T., & Poggio, T. A. (1996). Facial analysis and synthesis using image-based models. In *Proceedings of the Second International Conference on Automatic Face and Gesture Recognition* (pp. 116–121). Piscataway, NJ: IEEE.
- Farah, M. J., Tanaka, J. W., & Drain, H. M. (1995). What causes the face inversion effect?. *Journal of Experimental Psychology: Human Perception and Performance*, 21(3), 628.
- Goffaux, V., & Rossion, B. (2006). Faces are “spatial”—holistic face perception is supported by low spatial frequencies. *Journal of Experimental Psychology: Human Perception and Performance*, 32(4), 1023.
- Hershfield, H. E., Goldstein, D. G., Sharpe, W. F., Fox, J., Yeykelis, L., Carstensen, L. L., & Bailenson, J. N. (2011). Increasing saving behavior through age-progressed renderings of the future self. *Journal of Marketing Research*, 48(SPL), S23–S37.
- Jafri, R., & Arabnia, H. R. (2009). A survey of face recognition techniques. *Journal of Information Processing Systems*, 5(2), 41–68.
- Jones, M. J., & Poggio, T. (1996). *Model-based matching by linear combinations of prototypes*. (MIT AI Memo 1583). Cambridge, MA: MIT.
- Leopold, D. A., O’Toole, A. J., Vetter, T., & Blanz, V. (2001). Prototype-referenced shape encoding revealed by high-level aftereffects. *Nature Neuroscience*, 4(1), 89.
- Malpass, R. S., & Kravitz, J. (1969). Recognition for faces of own and other race. *Journal of Personality and Social Psychology*, 13(4), 330.
- Merler, M., Ratha, N., Feris, R. S., Smith, J. R. (2019). Diversity in Faces. arXiv:1901.10436.
- Olivola, C. Y., & Todorov, A. (2010). Elected in 100 milliseconds: Appearance-based trait inferences and voting. *Journal of Nonverbal Behavior*, 34(2), 83–110.
- Oosterhof, N. N., & Todorov, A. (2009). Shared perceptual basis of emotional expressions and trustworthiness impressions from faces. *Emotion*, 9(1), 128.
- Parke, F. I. (1974). *A parametric model for human faces* (No. UTEC-CSc-75-047). Utah University Salt Lake City Department of Computer Science.
- Rhodes, G., Brennan, S., & Carey, S. (1987). Identification and ratings of caricatures: Implications for mental representations of faces. *Cognitive Psychology*, 19(4), 473–497.
- Samal, A., & Iyengar, P. A. (1992). Automatic recognition and analysis of human faces and facial expressions: A survey. *Pattern recognition*, 25(1), 65–77.
- Schyns, P. G., Bonnar, L., & Gosselin, F. (2002). Show me the features! Understanding recognition from the use of visual information. *Psychological Science*, 13(5), 402–409.
- Shepard, R. N. (1962). The analysis of proximities: Multidimensional scaling with an unknown distance function. I. *Psychometrika*, 27(2), 125–140.
- Smith, M. L., Cottrell, G. W., Gosselin, F., & Schyns, P. G. (2005). Transmitting and decoding facial expressions. *Psychological Science*, 16(3), 184–189.
- Storrs, K. R., & Arnold, D. H. (2012). Not all face aftereffects are equal. *Vision Research*, 64, 7–16.
- Valentine, T. (1988). Upside-down faces: A review of the effect of inversion upon face recognition. *British Journal of Psychology*, 79(4), 471–491.
- Valentine, T. (1991). A unified account of the effects of distinctiveness, inversion, and race in face recognition. *The Quarterly Journal of Experimental Psychology Section A*, 43(2), 161–204.
- Wilson, H. R., Loffler, G., & Wilkinson, F. (2002). Synthetic faces, face cubes, and the geometry of face space. *Vision Research*, 42(27), 2909–2923.
- Yin, R. K. (1969). Looking at upside-down faces. *Journal of Experimental Psychology*, 81(1), 141.